Spatially-extrapolating subsampled airborne lidar: How much lidar is enough?

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Abstract

Airborne lidar snow depth retrievals are vital for water resource in basins with limited snow observations. However, airborne lidar remains impractical to collect frequently over large domains due to the high economic cost. In this study, we used lidar observations of snow depth across seven snow seasons in Tuolumne, CA to determine how well snow depth from subsampled lidar swaths could be extrapolated using snow depth distribution patterns from: 1) fully-distributed lidar observations in other snow seasons, 2) a satellite-trained SWE reconstruction product, and 3) the combination of the two. The framework (Figure 1) can be used to determine the extent of airborne lidar observations that are appropriate for any given basin, therefore optimizing snow-resource management.

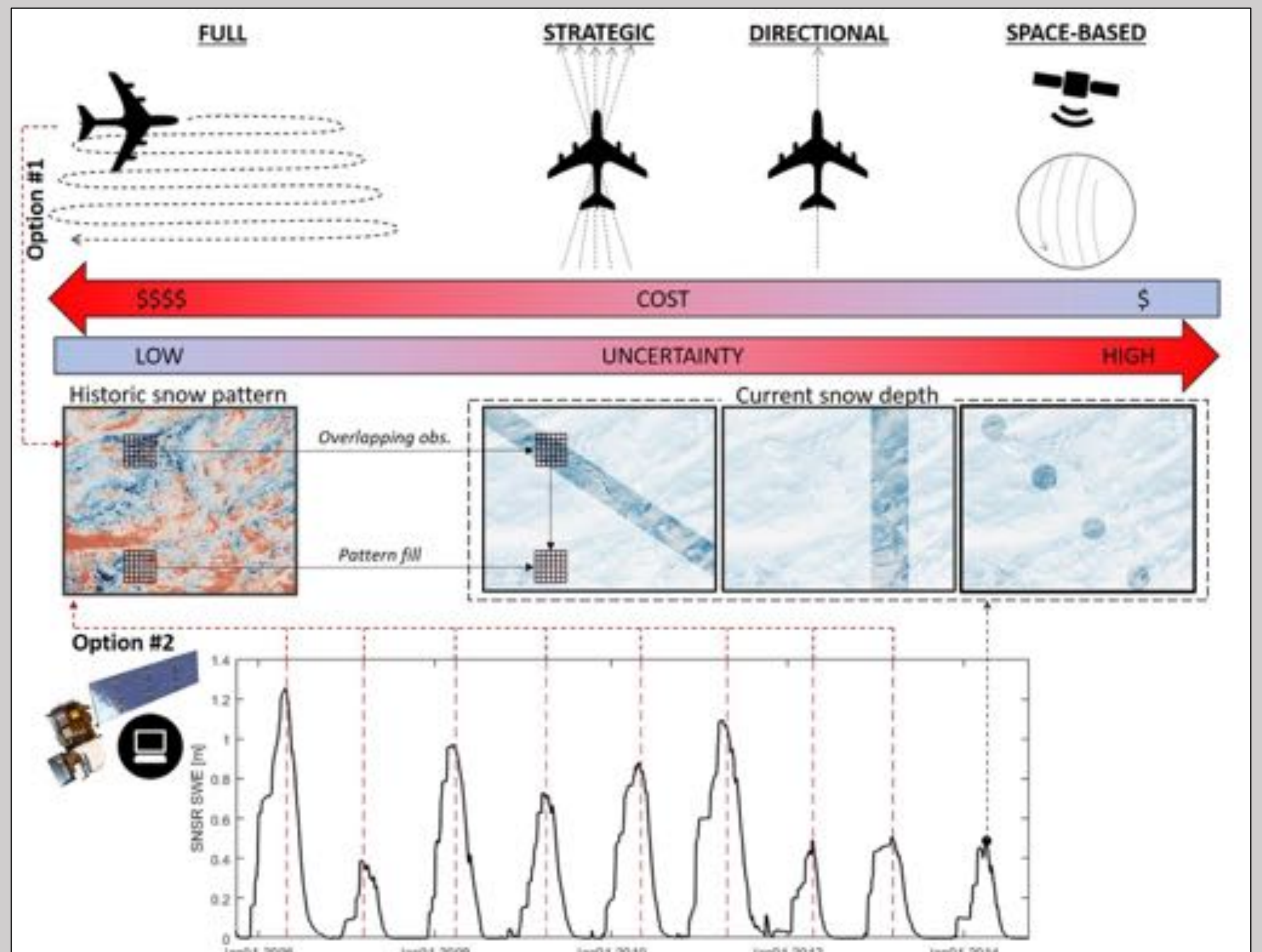


Figure 1. Overlapping observations and fully-distributed snow patterns from airborne lidar (option #1) and/or SWE reanalysis products (option #2) are used to extrapolate snow depth across a domain. Extrapolation performance is a function of both snow depth accuracy and the economic cost of the spatially-reduced observation (arrows).

Methodology

1. Airborne lidar observations (Painter et al., 2016) were subsampled to simulate flight swaths and satellite observations with various resolutions, spatial coverages, and orientations.
2. Snow pattern maps were created with fully-distributed datasets in other snow seasons using the standardized depth value (Sturm and Wagner, 2010),

$$\mathrm{SDV}_{\mathrm{ij}} = \frac{\mathrm{depth}_{\mathrm{ij}} - \overline{\mathrm{depth}}}{\sigma_{\mathrm{depth}}}. \quad (1)$$

3. Using the linear relationship between any subsampled lidar observation and overlapping snow pattern (Figure 1), domain-wide mean snow depth and standard deviation were derived and used to calculate a domain-wide inferred snow depth map (Figure 2).

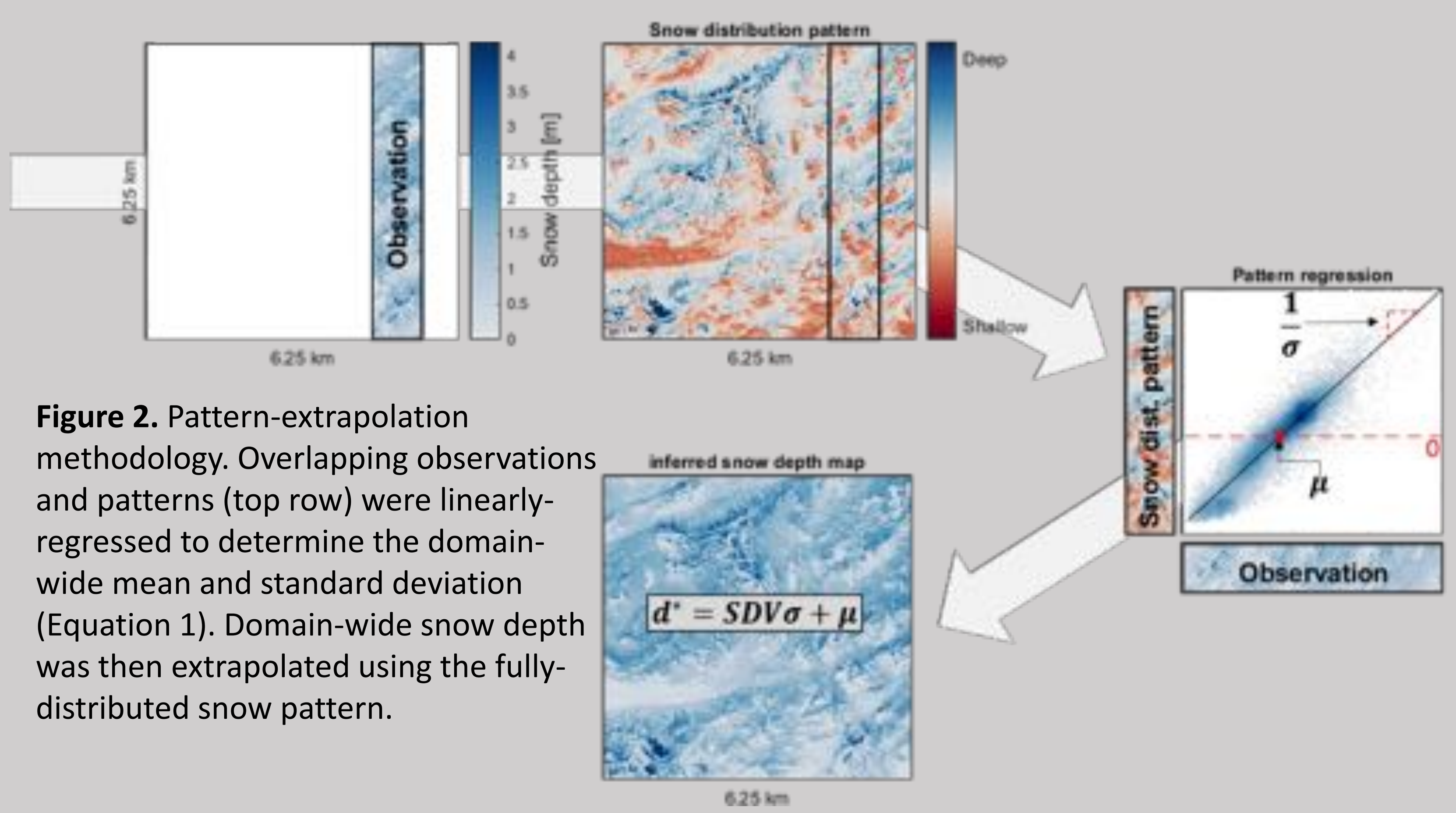


Figure 2. Pattern-extrapolation methodology. Overlapping observations and patterns (top row) were linearly-regressed to determine the domain-wide mean and standard deviation (Equation 1). Domain-wide snow depth was then extrapolated using the fully-distributed snow pattern.

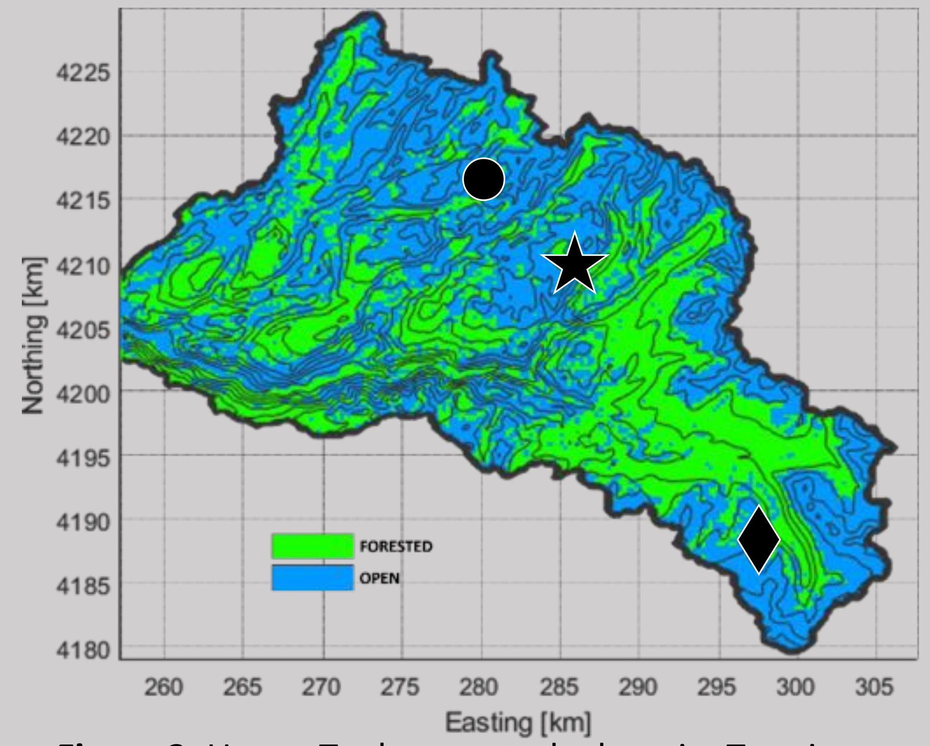
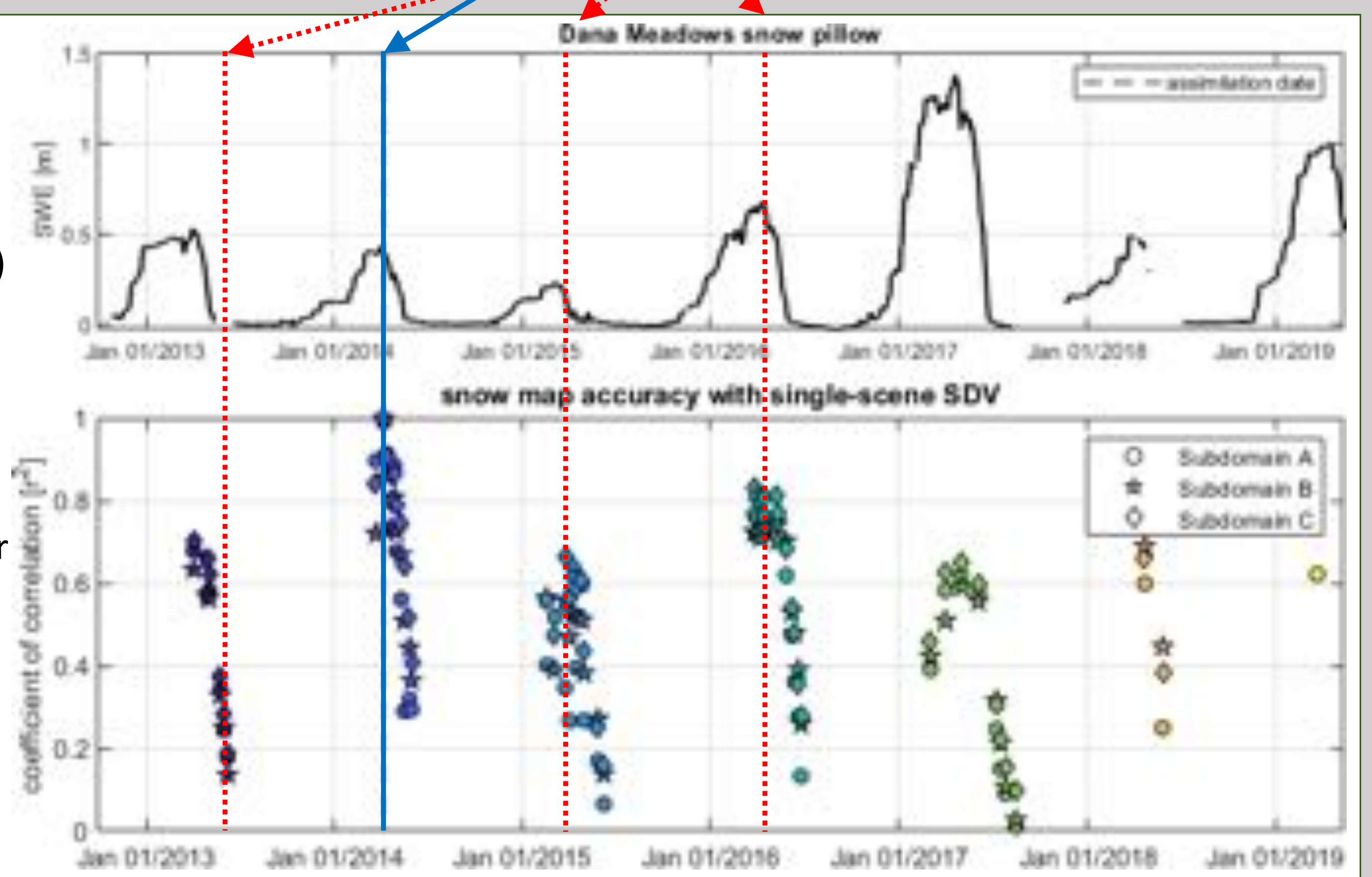


Figure 3. Upper-Tuolumne study domain. Terrain is represented by black contours with subdomains (Figure 4) indicated by symbols.

Study domain

Tests were performed across the upper-Tuolumne watershed within Yosemite National Park, CA (Figure 3) where 48 airborne lidar collections exist for seven snow seasons (WY2013-2019). This domain ranges between 700 – 3900 meters of elevation with approximately 36% forest coverage. While figure 4 depicts results at 100 m resolution across the entire domain, subdomains were also identified (Figure 3, symbols) to test snow-pattern persistence at 25 m resolution for various types of terrain (Figure 4).

Figure 4. Extrapolated depth map accuracy (bottom) provided a fully-distributed lidar observation on 7 April 2014 (blue line) and lidar swaths at all other times (x-axis). Mid-elevation snow pillow data is provided for reference (top).



Snow pattern persistence

Lidar-observed snow patterns with similar proximity to peak-SWE timing were persistent between snow seasons. In fact, the coefficient of correlation between snow patterns within approximately 20 days of each other (with respect to peak-SWE timing) was greater than 0.70 (e.g., Figure 3). Performance was increased by excluding abnormally wet water-year 2017 and abnormally warm water-year 2015.

Results

Swath observations in the direction of highest pattern variability outperformed random swath orientations.

Using snow patterns defined by a fully-distributed lidar collection:

- The extrapolated snow depth coefficient of correlation was > 0.70 and biased by < 5% for swaths at similar times (within 20 days) in typical snow seasons.
- Extrapolation performance degraded as a function of observation-pattern mistiming as accumulation and melt patterns were superimposed to varying degrees.

Using snow patterns defined by SNSR distributed SWE from all other seasons:

- Extrapolated snow depth bias was reduced by 70%, on average, as compared to patterns from only a single distributed lidar observation.
- Snow patterns were too homogeneous and therefore increased mean absolute error.
- Patterns could be adjusted using a single, fully-distributed lidar observation. However, this adjustment was typically most-effective at times with similar proximity to peak-SWE timing.

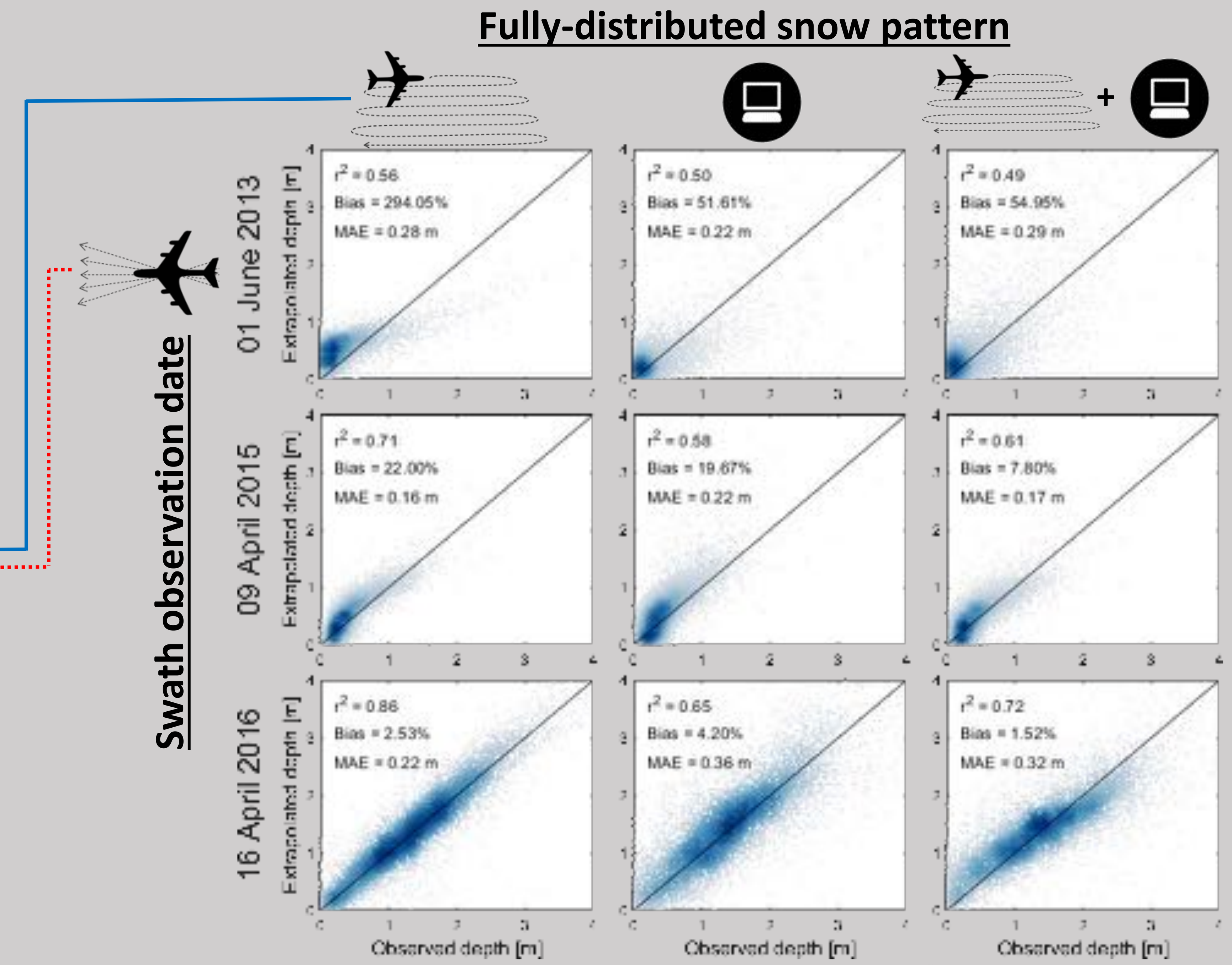


Figure 5. Extrapolated snow depth coefficient of correlation (r^2), bias, and mean absolute error MAE for swaths covering < 5% of the domain flown on a variety of dates (rows), using different snow patterns (columns).

Table 1. Advantages and disadvantages of various snow-pattern data sources.

PATTERN FROM:	PROS:	CONS:
	• Good representation of snow pattern heterogeneity • Can be used to train model deposition/melt patterns • Scalable to different resolutions	• Performance degrades for mistiming between the pattern and observation • Poor performance in abnormal snow seasons • Economically expensive
	• Good determination of basin-wide peak-SWE timing • Decreased sensitivity to observation timing • Economically cheap • Can inform ideal observation locations	• Patterns are too homogeneous
+	• Can correct modeled pattern homogeneity • Good determination of basin-wide peak-SWE timing • Can inform ideal observation locations	• Pattern corrections are constrained to a similar time in the snow season • Economically expensive

Conclusions and recommendations

Snow distribution patterns are persistent from season to season at similar points in the snow season. Therefore, annual airborne lidar observations could be optimized to 1) decrease the economic cost of domain-wide snow depth determination, or 2) determine snow depths over larger domains. Therefore:

- **Airborne lidar swaths should be flown in the direction of highest snow pattern variability at a time in the snow season that is similar to previous, fully-distributed lidar collections.**
- **Pairing pattern-assimilation with satellite-trained SWE reconstructions improves the derivation of domain-wide mean snow depth**
- **Snow patterns from only the SWE reconstruction product are preferable If patterns from fully-distributed lidar observations are unavailable or poorly-timed.**

Future snow campaigns should investigate snow-persistence and the applicability of this method in different snow regimes. While pattern-assimilation may reduce the cost of airborne lidar, we acknowledge that all airborne lidar collections are expensive. Therefore, the applicability of satellite-based snow depth observations should also be investigated (Figure 1).

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